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ABSTRACT

Applying commonality analysis to canonical correlation analysis is part of a trend toward the use of multivariate statistical methods enhanced by the ease of computation provided by computer software. Several recent papers have discussed canonical commonality analysis. This paper summarizes developments in the field and uses a data set to demonstrate how canonical commonality analysis sheds light on the interpretation of the model effect. The paper also provides guidelines for the deletion of predictors in canonical correlation analysis. Canonical commonality analysis honors the multivariate context and preserves the level of scale of the variables. It would be useful when the number of predictors is less than 5. An appendix contains the Statistical Package for the Social Sciences syntax for the canonical commonality analysis. (Contains 3 tables and 11 references.) (Author/SLD)

Running head: CANONICAL COMMONALITY ANALYSIS

Understanding Variance Contributions to Overall Canonical Correlation Effects: Canonical Commonality Analysis

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Paper presented at the annual meeting of the Southwest Educational Research Exchange, February 1-3, 2001, New Orleans.

Abstract

As the multivariate statistical methods enjoy its "blooming" in the last two decades because of the ease of computation provided by computer software, efforts also have been made to enhance the interpretation of its results. Applying commonality analysis to canonical correlation analysis, the most general multivariate linear model, is part of that trend. In a paper presented at the annual meeting of the Southwest Educational Research Association, Thompson & Miller generalized the commonality analysis for use in canonical correlation analysis (Thompson & Miller, 1985). Several papers, since then, have discussed different aspects of that extension—canonical commonality analysis. The present paper seeks to summarize the findings and, using a data set, to demonstrate how canonical commonality analysis sheds light on interpretation of the model effect and provides guideline for deletion of predictors in canonical correlation analysis.

Introduction

Multivariate statistical methods have been available to researchers for many decades, however, they were not used as frequently as it should be until the last twenty years. With reference to canonical correlation analysis, Thompson & Miller (1985, p.1) credit the revival of the utilization of multivariate statistics to "its computerization and inclusion in major statistical package." On top of the ease of access, researchers in social science also find multivariate methods appropriate, and even mandatory in some circumstance, in views of the intertwining nature of the factors involving in the phenomena under investigation. Campbell (1992, pp 1-2) goes into length to lay out the importance of utilizing multivariate statistics, quoting from other authors like Fish, Huberty & Morris, LeCluyse, and Thompson. She lists three reasons that call for multivariate statistics: (a) it controls the experiment-wise Type I error rates (b) It detects statistically significant results that univariate statistics may miss and actually exist (c) it best honors the complexities of reality. Campbell points to the third reason as the most important. The complexities of reality that call for multivariate models, in which causes have multiple effects and effects have multiple causes, present also difficulties in output interpretation. Researchers are not only interested in the overall effect of the model. They also need to know where does the effect come from, among the multiple causes, in order to interpret the output adequately. Commonality analysis has been proven useful in interpreting multiple regression output, as it helps researchers find out the unique and shared contributions from all the predictors in the regression model. Efforts have been made to extend it to multivariate analysis to enhance the interpretation of the results.

Knapp (1978) demonstrated that canonical correlation analysis as the most general parametric test that subsumes not only the multivariate analyses but all other parametric tests as special cases. Thompson (1988) illustrated, with a hypothetical data set, that canonical correlation analysis gives the same results as multiple regression. If canonical correlation analysis subsumes multiple regression as a special case, commonality analysis should be useful to the interpretation of its results just as it is useful for multiple regression. In a paper presented at the annual meeting of the Southwest Educational Research Association, he generalized the commonality analysis for use in canonical correlation analysis (Thompson & Miller, 1985). Several papers, since then, have discussed different aspects of that extension—canonical commonality analysis. The present paper seeks to summarize the findings and, using a data set, to demonstrate how canonical commonality analysis sheds light on interpretation of the model effect and provides guideline for deletion of predictors in canonical correlation analysis. A brief revision on commonality analysis should be a logical place to start. A mechanism of defining and computing the components of variance of the dependent variable regresses against k predictors will be discussed with example. Then, attention will be given to some important issues of doing commonality analysis. The latter part of the paper is devoted to implementation of commonality analysis in canonical case.

Commonality Analysis for Multiple Regression

Commonality analysis is a method for partitioning R^2 in multiple regression, the explained variance in the dependent variable, into constituents associated with the unique effects of each predictor variables and the common effects of any combination of the predictors. This method was originally suggested by Kempthorne in 1957. It has been called different names: "element analysis" by Newton and Spurrell, "components analysis" by Mayeske et al. The term "commonality analysis" was first used by Mood in 1971 (Daniel, 1989). Commonality analysis helps the researcher to identify the relative importance of all predictor variables in the regression model by showing the percentage of dependent variable variance contributed by each of them uniquely and by two or more of them commonly. The predictor variables in the model could be the independent variables representing the main effects or the product variables representing interaction effects. For the sake of clarity, regression model without product variables will be discussed first and leaves interaction effects for later discussion.

Defining and Computing Components of the D.V.'s Explained Variance

Each component in the partition of the explained variance of the dependent variable under commonality analysis associates with one or more of the k predictors in the regression model. Since the number of ways of choosing at least one object from k objects is 2^k-1, the commonality analysis of a k-predictor regression model has 2^k-1 components. Among those components, k of them depict unique effects and the remaining 2^k-k-1 of them are with common effects. For example, in a 2-predictor regression model, the number of components identified in commonality analysis is $2^2 - 1 = 3$. Let y be the dependent variable and a and b be the two predictors. The three components will then be U_a, U_b for the unique effects, and C_{ab} for the common effect. Since U_a is the variance associated only to a and not share with b, U_a can be calculated by subtracting from the explained variance R^2 the squared correlation between y and b with a partial out. U_b can be calculated in the similar way. C_{ab} can be easily found by subtracting U_a and U_b from R^2.

$$U_a = R^2 - R^2_{y.b}$$

$$U_b = R^2 - R^2_{y.a}$$

$$C_{ab} = R^2 - U_a - U_b$$

For model with three or more predictors, however, the procedure is not that straight forward. Wisler and Mood (1969) have developed a polynomial approach of writing commonality formulas for any number of predictor variables. Seibold and McPhee (1978) gave a step-by-step presentation of this approach and a summary of the computational formulas for calculating common effects in the two-, three-, four-, and five-predictor models.

This approach uses a product of k factors to represent each commonality component for k-predictor regression model. Two kinds of factors are included in the product, X_i and $(1 - X_j)$, where X_is represent those variables that do not involved in the unique or common effect under consideration, and X_js represent those variables that do. In a four-predictor model, for example, the product for C_{134}, the component common to variables 1, 3, 4, is $-(1 - X_1)X_2(1 - X_3)(1 - X_4)$, and the product for U_1, the unique effect of X_1, is $-(1 - X_1)X_2X_3X_4$. In general, for the commonality component C_{pqr}, associated with three predictors p, q, and r, of a k-predictor regression model, the product is, C_{pqr}: $-X_1\ldots(1-X_p)\ldots(1-X_q)\ldots(1- X_r)\ldots X_k$. The commonality component involved all predictors will be represented by $-(1 - X_1)(1 - X_2)\ldots(1 - X_{k-1})(1 - X_k)$. When each product is expanded, it becomes a polynomial with two to 2^k terms. Each term in these polynomials is a monomial of some X_rs, where $1 \leq r \leq k$. These polynomials are then transformed into formula for calculating the variance components. The terms in the polynomials are turned into squared part correlations between the dependent variable and the predictor variables included in that term with the rest of the predictor variables controlled, e.g., the variance component associated to the unique effect of X_1, namely U_1, is therefore calculated by: formula $U_1 = R^2 - R^2_{y.234}$ derived from polynomial: $-(1 - X_1)X_2X_3X_4 = X_1X_2X_3X_4 - X_2X_3X_4$ Where $X_1X_2X_3X_4$ points to the total explained variance, model R^2, involving all four predictor variables. $X_2X_3X_4$ points to $R^2_{y.234}$, the squared part correlation between y and predictors 2, 3, 4 with predictor 1 controlled. The squared part correlations can be obtained by the running multiple regression models that includes only the predictors that are involved in the part correlations. Rowell (1995) pointed out that SAS provides a useful procedure command (PROC RSQUARE) that prints out the R^2 values of all possible combinations of the independent variables in the model. This SAS procedure has greatly simplified the calculation of the variance components. Once the squared part correlations are obtained, the computation of the components is straightforward and involves only addition and subtraction. Formulae for computing commonality components of a three-predictor regression are given below as an example.

Components of Explained Variance in a Three-Predictor Regression Model

In the Venn diagram (fig.1), the rectangle represents the total variance in the dependent variable. The circle represents the part that explained by the predictors. The seven (2^3-1=7) commonality components associated to the three predictors partition the explained variance.

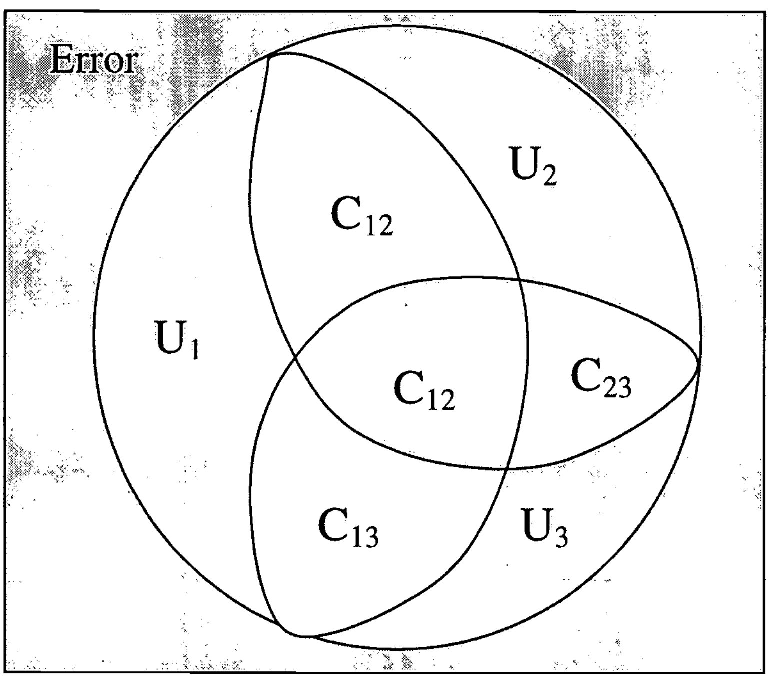

Figure 1. Unique and Common Components of Explained Variance in Regressions for Three Predictors

Following the polynomial approach, the components are:

U_1 : $-(1 - X_1)X_2X_3 = X_1X_2X_3 - X_2X_3$

$U_2: \ -X_1(1 - X_2)X_3 = X_1X_2X_3 - X_1X_3$

$U_3: \ -X_1X_2(1 - X_3) = X_1X_2X_3 - X_1X_2$

$C_{12}: \ -(1 - X_1)(1 - X_2)X_3 = X_1X_3 + X_2X_3 - X_3 - X_1X_2X_3$

$C_{13}: \ -(1 - X_1)X_2(1 - X_3) = X_1X_2 + X_2X_3 - X_2 - X_1X_2X_3$

$C_{23}: \ - X_1(1 - X_2)(1 - X_3) = X_1X_2 + X_1X_3 - X_1 - X_1X_2X_3$

$C_{123}: -(1 - X_1)(1 - X_2)(1 - X_3) = -1 + X_1 + X_2 + X_3 - X_1X_2 - X_1X_3 - X_2X_3 + X_1X_2X_3$

The formulae to compute the components are as follow:

$U_1 = R^2 - R^2_{y.23}$

$U_2 = R^2 - R^2_{y.13}$

$U_3 = R^2 - R^2_{y.12}$

$C_{12} = R^2_{y.13} + R^2_{y.23} - R^2_{y.3} - R^2$

$C_{13} = R^2_{y.12} + R^2_{y.23} - R^2_{y.2} - R^2$

$C_{23} = R^2_{y.12} + R^2_{y.13} - R^2_{y.1} - R^2$

$C_{123} = R^2_{y.1} + R^2_{y.2} + R^2_{y.3} - R^2_{y.12} - R^2_{y.13} - R^2_{y.23} + R^2$

Model with more predictors follows the same rule. Seibold and McPhee (1979) provide the formulae for models up to 5 predictors.

Issues of Commonality Analysis

There are several issues of commonality analysis need to be addressed. First of all, the number of components increases exponentially as the number of predictors in the model increase. It is practical to keep the number of predictors to four or fewer. This may be accomplished by grouping of variables, or selecting best predictors through a series of preliminary analyses, e.g. through factor analysis. In the grouping of variables, theoretical support and the natural relationship of the variables should be concerned. Second, Distinction between common effects in the partition of variance and interaction effects in the regression model should be maintained. Interaction is the unique effect of two or more independent variables that in combination affect the dependent variable. Commonality indicates the proportion of predictive ability of a single variable that also happens to reside in another single predictor variable too; no unique effect of the predictors acting in combination is involved (Thompson, 1985). The difference between the interaction effect and common effect is demonstrated by fig.2 and fig.3 below. In fig.2 the interaction effect predictors 1 and 2 is represented in the model by a product variable 1*2, which is treated as a third predictor, U_{1*2}. In the explained variance there are components common to the main effect predictors and the interaction effect predictor. On the other hand, there is only common effect in fig.3. The variance associated with the interaction effect is now part of the unexplained or error variance.

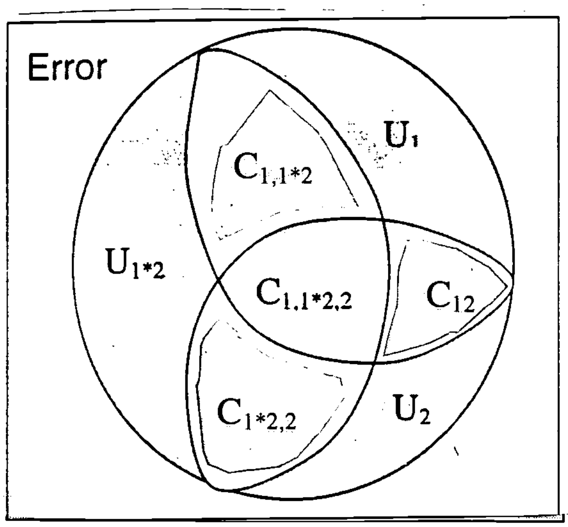

Figure 2. Regression model with interaction effect presented.

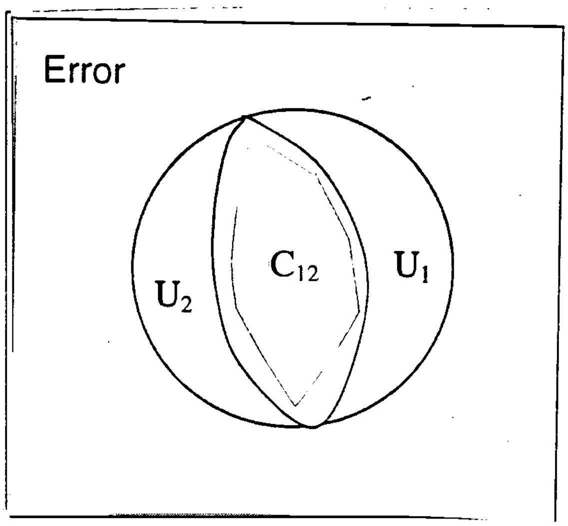

Figure 3. Regression model with main effects only

Finally, it should be noted that negative commonality might occur. Negative commonality frequently indicates the presence of suppressor effect. It happens when highly correlated variables affect each other in opposite directions. That explains why sometime the unique contribution of a predictor to the explained variance is bigger than the overall contribution of that predictor when another predictor is presented in the model.

Canonical Commonality Analysis

Tabachnick and Fidell (1996, p.195) maintain "the easiest way to understand canonical correlation is to think of multiple regression." In multiple regression, several variables on one side are combined linearly to predict a single variable on the other side. The linear composition of variables applies also to canonical correlation except that there are several variables on both sides. In the simplest terms, canonical correlation analysis is a way to assess how two sets of variables relate to each other. The canonical correlation, the model effect, is the correlation between the pair of composites of variables that are most highly correlated. There could be as many pairs of variable composites, which are called canonical functions or variates, as the number of variables in the smaller set of the two. Canonical commonality analysis is applying commonality analysis to partition the variance of a variate of a set of variables (conveniently called the criterion variate) associated to the variables in the other set (conveniently called the predictor variables). It is an extension of the commonality analysis in multiple regression. Since canonical correlation is a symmetrical measure, the relation can be stated in both directions. The difference here is that instead of applying the analysis to the variance of one dependent variable, it is applied to a variate, a linear composite of a set of variables. A partial set of variables from the Holzinger's data is used here to demonstrate the steps of doing the analysis and the interpretation of the results.

An Example

The data used here is a part of the Holzinger's study on ability batteries of 301 students. Two sets of are chosen, t5, t6, t9 on one side and t20, t22, t24 on the other. The descriptions of the variables are as follow:

T5 GENERAL INFORMATION VERBAL TEST

T6 PARAGRAPH COMPREHENSION TEST

T9 WORD MEANING TEST

T20 DEDUCTIVE MATH ABILITY

T22 MATH WORD PROBLEM REASONING

T24 WOODY-MCCALL MIXED MATH FUNDAMENTALS TEST

The first group of variables measures verbal ability, and the second group measures math problem solving ability in general. Canonical correlation analysis will be run to find out the relationship between the math problem solving ability and verbal ability, and then commonality analysis will be performed to help to shed light to the interpretation.

Steps of Canonical Commonality Analysis

The first step in Canonical Commonality Analysis is to run the canonical correlation analysis. The syntax of the SPSS canonical correlation analysis program is presented in appendix A. Three pairs of variates are created. The dimension reduction analysis shows that only one variate on the criterion side has significant effect size. Since the effect size decreases from variate 1 to variate 3, only variate 1 has a significant effect size. Therefore, the rest of the analysis will be performed on variate 1 only. Table 1 gives the summary of the analysis on variate 1.

INSERT TABLE 1 ABOUT HERE

The canonical correlation for the pair of variate 1 is 0.37883. Which means that about 38% of the variance in the criterion variate 1 is explained by the predictor variables t5, t6, and t9 as a group. From the adequacy coefficients and the squared structural coefficients, one can see that both groups of variables contribute highly to the variance in their respective composite variables, i.e. the criterion variate and the predictor variate. The unique or common contribution of individual predictors on the criterion's variance, however, can't be determined. All one can says with the information acquired thus far would be the verbal ability variables together predict about 38% of the math problem solving ability. Commonality analysis is in place here to help to find out the contributions of individual predictors.

The aim of canonical commonality analysis is to understand the partition of variance of the criterion variate explained by the predictors. The second step of the analysis is, therefore, to compute the criterion variate scores. The standardized canonical coefficients (labeled Func in table 1) and the standard scores of the dependent variables are used to compute the criterion variate scores using the formula: CRIT1 = -.264 * zt20 + -.561 * zt22 + -.461 * zt24. (Please refer to appendix A for the SPSS syntax). The criterion variate score for each of the 301 students is computed and saved under the variable name CRIT1.

The third step of the canonical commonality analysis is to conduct multiple regressions on the variates using all possible sets of predictors. There are seven ($2^3 - 1 = 7$) possible combinations of using at least one of the three predictors in the multiple regressions. In SPSS, the regressions have to be run one by one. There is a useful procedure command in SAS, PROC RSQUARE that allow the user to compute all those regressions in one shot. For this example, The SPSS syntax for the regressions run is also given in appendix A. The R^2s are presented in table 2.

INSERT TABLE 2 ABOUT HERE

Step four is to compute the commonalities by substituting the value of the R^2 s into the commonality formulae in p.8. The result is tabulated in table 3. From table 3, all of the predictors have very small unique effect, e.g. unique effect of predictor t5 is only 0.002 that is only 0.2% of the total variance in the variate CRIT1 and is about 0.5% of the explained variance. The effect common to any two of the three predictors are not big either, e.g. the commonality associated with t5 and t6 is only 0.7% of the total variance in CRIT1 and is about 1.85% of the explained variance. The major contribution to CRIT1 is from the three-way commonality, which is 20.6% of the total variance and over 50% of the explained variance.

INSERT TABLE 3 ABOUT HERE

It is interesting to see from the bottom of table 3 that t5, t6, and t9, explained 24.8%, 29.4%, and 34.4% of the variance in CRIT1 respectively (they can also be find in table 2 as the R^2 of the multiple regressions using one predictor), and to go up table 3 and see that the unique explanatory ability of the three predictors are actually .2%, 2.6% and 5% only. It is found through commonality analysis that the three predictors share most of their predicting power. Among the three predictors, t9 contributed most to the variance in CRIT1. Since the three predictors shared most of their predicting power, t9 by itself would do a good enough job as the predictor for CRIT1.

Discussion

From the above example, one can see the value of doing commonality analysis. It tells where exactly the effects fall on. Thompson (1985) and Daniel (1989) also point out that canonical commonality analysis honors the multivariate nature of the dependent variables, and examines their effects without taking them out of the multivariate context. Attempts of interpreting other statistics from the canonical correlation analysis have been made in the past. But the canonical correlation is the only true multivariate effect. The interpretation of the pairs of variates involves several aspects. First, R_c, the canonical correlation gives the strength of the relationship between variates in each pair. Second, the adequacy coefficient on a variate, which is the average of the squared structural coefficients of the variables that generate the variate, shows how strong the variables related to the variate of its own set. Third, the redundancy index of a variate, which is the product of the squared canonical coefficient and the adequacy coefficient, gives the percent of variance explained by the variables in the other set of variables together. Together these pieces of information portrait how the two sets of variables relate within and across sets. Adequacy coefficients are obviously univariate statistics. Roberts (1999) has cited proof that redundancy indexes are also univariate. They shouldn't be utilized to interpret the multivariate result of canonical correlation analysis. Roberts also points out that the canonical correlation, rather than the redundancy index was maximized in the analysis, and should be the statistics for interpretation.

In order to simplify the analysis, researchers want to use fewer variables to give similar magnitude of model effect size. According to the law of parsimony, the simpler the explanation, the higher the probability of replicating the result and the more likely the explanation is to be true. Canonical commonality analysis could also provide guideline for deletion of predictors in Canonical correlation analysis. In the above example, if t5 is deleted, the predicting power of U_1 will be lost, but the effect size only reduces by .002. If both t5 and t6 are deleted, the predicting power of U_2 and C_{12} will also be lost, but the effect size only reduces to .344. In this case t9 predicts almost as well as all three predictors together.

Overall, With the ability to decompose explained variance to parts associated uniquely and commonly with predictors, and the straightforward calculation, commonality analysis can be very helpful to researcher seeking to know more about the effect of their regression analysis. Canonical commonality analysis helps to interpret the canonical correlation analysis effect and sheds light to the contributions of individual predictors. It honors the multivariate context and preserves the level of scale of the variables and would be useful when the number of predictors is less than 5.

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Table 1

Canonical Correlation Analysis Summary on Variate 1

Variable/	Variate 1		
Statistics	Func	Struc	$Stru^2$
T20	-.264	-.637	40.58%
T22	-.561	-.849	72.08%
T24	-.461	-.772	59.60%
Adequacy			57.43%
R_d			21.76%
R_c^2			37.88%
R_d			29.51%
Adequacy			77.90%
T5	-.115	-.809	65.45%
T6	-.386	-.881	77.62%
T7	-.595	-.952	90.63%

Table 2

R^2 of the multiple regressions of CRIT1 with at least one of the three predictors

	Predictors	R^2 value
$R^2_{y.1}$	t5	.248
$R^2_{y.2}$	t6	.294
$R^2_{y.3}$	t9	.344
$R^2_{y.12}$	t5, t6	.329
$R^2_{y.13}$	t5, t9	.353
$R^2_{y.23}$	t6, t9	.377
$R^2_{y.123}$	t5, t6, t9	.379

Table 3

Commonality Analysis Summary Table for CRIT1

Unique /Commonality	T5	T6	T9
U_1	.002		
U_2		.026	
U_3			.050
C_{12}	.007	.007	
C_{13}	.033		.033
C_{23}		.055	.055
C_{123}	.206	.206	.206
Total	.248	.294	.344
Commonality	.246	.268	.294
R^2 explained by	24.8%	29.4%	34.4%

APPENDIX A

SPSS Syntax Used to Do the Canonical Commonality Analysis

```
TITLE 'Canonical Commonality Analysis'.

COMMENT data used is taken from Holzinger & Swineford (1937).
COMMENT Run Canonical Analysis Using SPSS MANOVA command.
MANOVA
        t20 t22 t24 WITH t5 t6 t9
        /PRINT=SIGNIF (MULTIV EIGEN DIMENR)
        /DISCRIM= (STAN CORR ALPHA (.999)).

COMMENT create the z-scores for the six variables.
DESCRIPTIVES
 VARIABLES=t20 t22 t24 t5 t6 t9 /SAVE
 /STATISTICS=MEAN STDDEV MIN MAX .

COMMENT compute and save the criterion variate scores for canonical function 1.
COMPUTE CRIT1 = -.264 * zt20 + -.561 * zt22 + -.461 * zt24.
EXECUTE .

COMMENT Run regressions of all possible combinations of the three predictors to find the part
correlations for commonality analysis.
REGRESSION
 /MISSING LISTWISE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT crit1
 /METHOD=ENTER t5 .
REGRESSION
 /MISSING LISTWISE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT crit1
 /METHOD=ENTER t6 .
REGRESSION
 /MISSING LISTWISE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT crit1
 /METHOD=ENTER t9 .
REGRESSION
 /MISSING LISTWISE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT crit1
 /METHOD=ENTER t5 t6 .
REGRESSION
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 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT crit1
 /METHOD=ENTER t5 t9 .
REGRESSION
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 /CRITERIA=PIN(.05) POUT(.10)
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